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Ground-Sensor Soil Reflectance as Related to Soil Properties and Crop Response in a Cotton Field

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Abstract. Bare soil reflectance from airborne imagery or laboratory spectrometers has been used to infer soil properties such as soil texture, organic matter, water content, salinity and crop residue cover. However, the relation of soil properties to reflectance data often varies with soil type and conditions and surface reflectance may not be representative of the conditions in the root zone. The objectives of this study were to assess the soil reflectance data obtained by ground-based sensors and to model soil properties in the root zone as a function of surface soil reflectance and plant response. Ground-based sensors were used to simultaneously monitor soil and canopy reflectance in the visible and near-infrared (VNIR) along six rows and in two growth stages in a 7 ha cotton field. The reflectance data were compared to soil properties, leaf nutrients and biomass measured at 33 sampling positions along the rows. Brightness values of the blue and green bands of soil reflectance were better correlated to soil water content, particulate organic matter and extractable potassium and phosphorus, while those in the red and NIR bands were correlated to soil carbonate content, total nitrogen, electrical conductivity and foliar nutrients. The correlation of red soil reflectance with canopy reflectance was significant and indicated an indirect inverse relationship between soil fertility and plant stress. The integration of surface soil reflectance and plant response variables in a multiple regression model did not substantially improve the prediction of soil properties in the root zone. However, crop nutrient status explained a significant portion of the spatial variability of soil properties related to nitrification processes when soil reflectance did not. The implication of these findings to agricultural management is discussed.

Keywords: canopy reflectance, NDVI, spatial variability, crop nutrients, biomass

Introduction

Spectral reflectance has been used to infer soil properties primarily in the visible and near-infrared (VNIR) and in the shortwave-infrared (SWIR) regions. Bare soil reflectance in these spectral regions has been obtained from airborne imagery or spectrometers under laboratory conditions and has been mainly related to soil texture, organic matter and associated nutrients, water content, salinity and crop residue cover. An extensive review of the literature about these relationships is provided by Barnes *et al.* (2003). However, inference of soil properties from bare-soil imagery for application to agricultural management can be constrained by their interaction with soil reflectance over a range of soil types and conditions. Furthermore, surface soil reflectance may not be representative of soil properties in the root zone. Therefore, there is a need to integrate other data sources and approaches before reliable methods can be developed to translate bare soil reflectance into maps of soil properties (Barnes *et al.*, 2003).

In this respect, crop response can be used as an aid in soil mapping because it provides an integrated measure of soil conditions that influence plant growth in the root zone. Crop response to conditions in the root zone is represented by crop nutrient status and biomass production. Canopy reflectance in the VNIR region of the spectrum, as obtained from satellite or aircraft imagery, has been used successfully as a tool to monitor changes in biomass production of vegetation at field and regional scales (Doraiswamy *et al.*, 2003). Furthermore, good relationships have been obtained between canopy spectral reflectance and N deficiencies of major agricultural crops such as wheat (Stone *et al.*, 1996) and corn (Blackmer *et al.*, 1996; Bausch and Diker, 2001). More recently, cotton yield has also been related to canopy reflectance obtained from a portable radiometer (Li *et al.*, 2001) or from satellite imagery (Wiegand *et al.*, 1991; Thomasson *et al.*, 2001).

Traditionally, approaches to site-specific management have involved grid sampling data, yield maps, aerial photographs, satellite images, electrical conductivity maps, and elevation maps to provide digital information to generate management zone and application maps using geospatial statistics and GIS tools. These input maps and images could have spatial resolutions ranging from 1 to 100 m. Integrating such maps and images into management zone and application maps requires combining sets of high-resolution cells and re-sampling coarse-resolution cells. Resultant maps have the advantage that they can be analyzed and processed at the leisure of the user, but this approach usually limits the inputs to soil-based information and historic yield data. Satellite information cannot usually be turned around quickly enough to aid in real-time management decisions. Aircraft imagery greatly improves the potential for acquiring timely spatial information, provided the aircraft is available when desired and the weather is conducive to obtaining a cloud-free photograph or image.

Ground-based sensors offer the possibility of collecting real-time plant and soil information that can be used to make management decisions without first developing a map. Such single pass operations (i.e., sensing and treatment) still require an algorithm or model to quantify the treatment. The basis for such algorithms begins with establishing relationships between a treatment and inputs from real time plant and soil sensors. Raun *et al.* (2002) have demonstrated a realtime plant sensor system for making N fertilizer applications to wheat. Their system does not involve soil-based information other than what is indirectly sensed through the plant canopy (vegetative cover and tissue color). It is conceivable that input from soil-based sensors could provide useful information when making nutrient applications. This type of soil sensing would provide much higher resolution information than is feasible with soil sampling or most imagery. Sudduth and Hummel (1993) used an early version of an NIR portable spectrophotometer to predict soil organic matter

(SOM) content across a range of soil types and moisture contents, but found that mobilizing the device introduced unacceptable errors in the field. Later they successfully developed an NIR sensor with faster data collection capabilities to estimate SOM and water content across a wide geographic area (Hummel *et al.*, 2001). Ultimately, once scientists come to understand the capabilities of ground-based plant and soil sensors, it should be possible to interpret the data and integrate the information into management decisions. The specific objectives of this study were: (1) to assess the ability of the sensors to predict key soil properties, (2) to investigate the relationship between soil reflectance and plant response in terms of canopy reflectance, crop nutrient status and biomass and, (3) to model soil properties in the root zone as a function of surface soil reflectance and plant response.

Materials and methods

The experimental field was located near the village of Moschochori in the municipality of Nikea (Larissa, Greece) at the coordinates 39°29′51.18″ N and 22°32′36.42″ E and covers an area of 7 ha. The east and west sides of the field were separated by a waterway running in a south-to-north direction. The soil on the east side is classified as a Typic Xerochrept and that on the west side as a Typic Xerorthent both with a clay texture. The soil near the waterway was finer in texture and was classified as Vertic Xerochrept.

The same management practices were applied to both sides of the field. The field was ploughed to a depth of 250 mm in the fall of 2000. Row spacing was 0.95 m and plant density was ~140,000 plants ha^{-1} (2–15 plants m^{-1}). Basic nitrogen and phosphate fertilization was applied at rates of 120 kg N ha^{-1} (96 kg ammonium and 24 kg nitrate) and 60 kg P_2O_5 ha^{-1} at 10 days before sowing in mid-April 2001. The following pesticides and herbicides were applied to the crop: phorate to the seed (10 kg ha^{-1}), prometryne (10 kg ha^{-1}) on the soil surface after sowing, endosulfan (3 kg ha^{-1}) at first bloom on July 20 and 2 to 3 sprays of pyrethrine in combination with acaricides thereafter. Groundwater was supplied to the plants by drip irrigation and on occasion by spraying with a mobile unit. With the exception of a rainy period in May, the summer period was dry and warm with only 140 mm of rainfall in July and August, a mean temperature of 27 °C (19–36 °C average daily min–max), and a mean relative humidity of 44% (20–70%).

Six strips were chosen across the length of the field on an east-west direction in order to include different soil colors as indicated by color aerial photography taken in May (Figure 1). Soil coloration has been shown to be related to organic matter content and soil productivity (Francis and Schepers, 1997; J.W. Doran, pers. comm.). Following preliminary soil sampling, a total of 33 sampling positions were selected along the strips based on a grid sampling design (30 m × 30 m). The coordinates of each position were recorded by a differential GPS (Fugro 3000L, OmniStar BV, Leidschendam, NL).

Multi-spectral Crop Circle (Holland Scientific, Lincoln, NE, USA) sensors were mounted in front of a tractor vehicle and used to measure reflectance at four

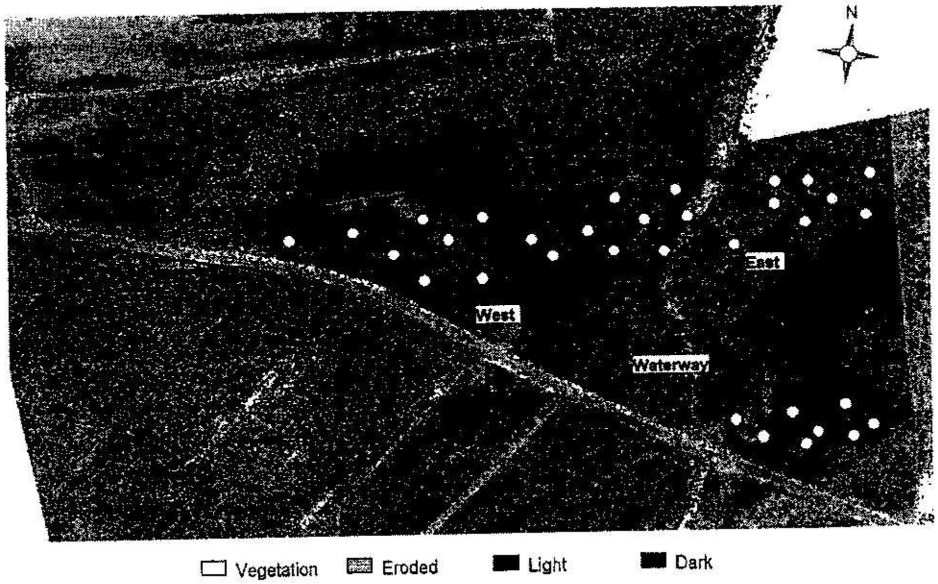

Figure 1. Processed aerial image of the cotton field just after sowing. Shown are the spatial distribution of the different categories of bare soil color and the sampling positions that are distributed along six rows based on a grid sampling design.

wavelengths (blue at 460 $\pm$ 10 nm, green at 550 $\pm$ 10 nm, red at 680 $\pm$ 10 nm, and NIR at 800 $\pm$ 65 nm) at an oblique view (30° from nadir) approximately 0.5 m from the target and a 0.25 m diameter field of view. One sensor was targeted at the ground between the rows and recorded bare soil reflectance early in the growing season (mid square) before the canopy was fully developed. A second sensor, at the same distance above the soil surface, recorded canopy reflectance along the cotton rows at mid square (late June) and peak bloom (late July). NIR values greater than 0.35 for the soil sensors and less than 0.35 for the canopy sensors were interpreted as non-target effects and thus were removed from the data set. The Normalized Difference Vegetation Index (NDVI) was computed from the data collected by the canopy sensor as: NDVI = (NIR-red)/(NIR + red). Due to compatibility problems of the GPS device with the sensors, the alignment of sensor readings with each sampling position was estimated. This was achieved using the known distances between sampling positions and assuming that the tractor was moving at a constant speed of 3.6 km h^{-1} while collecting 4 readings per meter of forward travel (250 ms shutter speed).

Soil and leaf samples were taken randomly from within a 5 m radius around each sampling position. Six composite surface soil samples (0–0.3 m) were taken with an Oakfield-type soil sampler at the end of June and September of 2001. At the end of June, July and August 2001, leaf samples from ~25 plants were taken from each sampling position (the fourth healthy unfolded leaf from the top, Reddy *et al.*, 2001). Five plants were randomly chosen from each sampling position in mid-September for the determination of above-ground biomass, open/closed bolls and lint production.

Soil samples were sealed in plastic bags and transported to the laboratory in a portable cooler. They were weighed, mixed and passed through a 2 mm sieve. Standard soil quality analysis included water content (w/w), bulk density, pH, electrical conductivity (EC) and nitrate and ammonium content in soil extracts of 1 M potassium chloride using an ion chromatograph (DX-120, Dionex Corporation, Sunnyvale, CA, USA) adjusted to a 1:1 soil-water ratio (Smith and Doran, 1996). Carbonate content was determined using GC analysis (Hewlett Packard Micro-GC equipped with a thermal conductivity detector, Hewlett Packard, Wilmington, DE, USA) of evolved CO_2 with in sealed containers upon addition of hydrochloric acid (Kettler and Doran, 1995). Macronutrients and trace elements (Ca, K, Mg, P, S, Zn) were determined by inductively coupled plasma spectrometry (Iris Advantage, Thermo Jarrell Ash, Franklin, MA, USA) after extraction of soil samples with a multiple extraction solution (Soltanpour and Schwab, 1977). Total nitrogen and carbon content, as well as isotopic composition ($\delta^{15}N$, $\delta^{13}C$) of soil samples (20 ± 0.1 mg), were measured by an automated combustion elemental analyzer interfaced with a triple collector isotope ratio mass spectrometer (IRMS, PDZ Europa, Crewe, UK). Organic carbon of selected soil samples was determined by the method of wet oxidation by Walkley-Black (Nelson and Sommers, 1982).

Leaf samples were transported to the laboratory in paper bags. Leaves were dried at 65 °C and subsequently ground to a fine powder. Macronutrients and trace elements (Ca, K, Mg, P, S, Zn) were determined by inductively coupled plasma spectrometry after digestion with concentrated nitric acid in a microwave system (Mars 5, CEM Corporation, Matthews, NC, USA). Total nitrogen and carbon content, as well as isotopic composition ($\delta^{15}N$, $\delta^{13}C$), of leaf samples (2.8 ± 0.1 mg) were measured by IRMS as described previously. Samples were prepared as described by Schepers *et al.* (1989).

Due to the large number of measured soil and plant variables, Pearson correlation and stepwise multiple regression was performed to identify relationships of soil properties with reflectance data, leaf nutrients and cotton biomass. The independent variables of the regression model were selected by eliminating gross multicollinearity and irrelevant variables so that at least 10 degrees of freedom remained for estimation of the error term. The regression model was checked by appropriate diagnostic procedures (collinearity and influence diagnostics). All procedures are reported in the Statistical Analysis System (SAS Institute, 1990).

Results and discussion

The spatial variability of the various soil properties was investigated and summarized (Table 1). Within-field variability was high for carbonates, particulate organic matter and for soil properties that are related to crop nutrient availability such as EC, nitrate-N and extractable P, K, S and Zn (Table 1). Differences in property values between sampling positions were as high as 20-fold for carbonates, nitrate-N, P and Zn. Soil pH, EC and NO_3-N were highly correlated with each other

Table 1. An overview of the variability of soil properties within the cotton field

Soil property	Mean	Min	Max	Ratio (Max:Min)	CV (%)
Bulk density (t m^{-3})	1.23	1.02	1.63	1.6	9
Water content (g g^{-1})	0.19	0.14	0.27	1.9	19
pH	8.1	7.8	8.3	1.1	2
EC (ds m^{-1})	0.73	0.42	1.20	2.9	31
NO_3-N (kg ha^{-1})	77	8	171	21.4	46
CO_3-C (mg g^{-1})	10	1	20	20.0	64
TVS (%)	41.5	32.5	51.2	1.6	13
POM (mg g^{-1})	98.0	47.3	158.5	3.4	28
N (kg ha^{-1})	2512	1772	3257	1.8	12
$\delta\ ^{15}N$ (‰)	8.71	7.61	9.19	1.2	4
P (kg ha^{-1})	4.6	0.7	12.8	18.3	58
K (kg ha^{-1})	98.8	507	1639	3.2	32
S (kg ha^{-1})	49.0	20.2	83.8	4.1	32
Ca (kg ha^{-1})	1634	1117	2655	2.4	19
Mg (kg ha^{-1})	582	344	837	2.4	21
Zn (kg ha^{-1})	14.5	1.4	31.6	22.6	63

(R^2 > 0.64, n = 33). The correlation of soil pH with EC and NO_3-N was negative due to soil acidification. Soil acidification is known to occur from nitrification of ammonium contained in inorganic fertilizers and the build-up of nitrate causes a rise of soil EC (Smith and Doran, 1996; Stamatiadis *et al.*, 1999). The more fertile soil on the east side of the field had higher water content, EC, nitrate-N and K concentrations and lower pH and carbonate content in June (Table 2). These differences in soil properties between the two sides of the field were amplified by the application of fertilizer N as there was evidence of fertilizer surface leaching from the west side during a rainy period in May. This rainy event was probably the reason for higher soil EC and nitrate-N and lower pH near the waterway (Table 2).

Several correlations were obtained between soil surface reflectance and soil properties in the 0–0.3 m depth. These correlations improved (Table 3) after removing from the data set four soil reflectance values that corresponded to sampling positions near the edges of the field. These positions received additional irrigation water by a spraying gun and the increased soil water content between the rows resulted in reduced soil reflectance in the red and NIR bands. The blue and green region of the spectrum had distinctively different correlation patterns to soil properties from the red and NIR bands. Soil water content, particulate organic matter (POM), K and P were linearly related to soil reflectance in the blue and green region of the spectrum (Table 3). Sampling positions on the east side of the field had higher water content, POM and associated inorganic nutrients that reduced blue and green reflectance and resulted in negative correlations (Figure 2). Soil water and organic matter content have been reported in the literature to be inversely related to both visible and NIR soil reflectance. Correlation of water content to visible and NIR reflectance of bare-soil fields was obtained when the data were taken a few days after rainfall (Milfred and Kiefer, 1976). Lobell and Asner (2002) and Weidong *et al.* (2002) found a non-linear dependence of water content to soil reflectance at various

Table 2. Variability of selected soil properties (0–0.3 m depth) across the cotton field in June, 2001

Soil properties		Landscape position		
		East side (n = 12)	Waterway (n = 4)	West side (n = 17)
Physical	Bulk density, g cm^{-3}	1.20	1.33	1.23
	Water content, g g^{-1}	0.22a	0.19b	0.17b
	WFPS*, %	48	53	40
Chemical	pH	8.03b	7.90c	8.17a
	EC, dS m^{-1}	0.87b	1.02a	0.56c
	NO_3-N, kg ha^{-1}	92.2b	139.0a	52.1c
	CO_3-C, %	0.55b	0.78b	1.44a
	N, kg ha^{-1}	251.6	2662	2473
	$\delta^{15}N$, %	8.563	8.730	8.801
	K, kg ha^{-1}	1570a	1123b	1112b
	P, kg ha^{-1}	5.1	4.6	4.8

*Water-filled pore space = (volumetric water content * 100)/soil porosity.
Means within rows followed by different letter(s) are significantly different at: $P < 0.05$.

NIR bands of the spectrum. Similarly, SOM has been related to reflectance data in the VNIR bands (Henderson *et al.*, 1992; Varvel *et al.*, 1999), while predictions were improved for organic C from different parent materials in the middle infrared bands (Henderson *et al.*, 1992). Sudduth and Hummel (1993) reported poorer predictions of SOM in the visible spectrum as compared to the range between 1720 and 2380 nm with a portable spectrophotometer. Our data show that the correlation of water

Table 3. Significant correlation coefficients (r, $P < 0.05$) of soil reflectance with soil properties, leaf nutrients and cotton yield (n = 27)

	Soil Reflectance			
	Blue	Green	Red	NIR
Soil properties (June)				
Water content	−0.74*	−0.76*	−0.56*	−0.59*
POM	−0.68*	−0.68	−0.45	−0.45
K	−0.80*	−0.82*	−0.56*	−0.59*
P	−0.57*	−0.61*	−0.51*	−0.50*
N	ns	ns	−0.57*	−0.40
CO_3-C	0.55*	0.65*	0.84*	0.73*
EC	ns	−0.45	−0.50*	−0.68*
Leaf nutrients (July)				
Zn	0.75*	0.78*	0.75*	0.55*
P	−0.48	−0.59*	−0.79*	−0.76*
N	ns	−0.45	−0.61*	−0.66*
Cotton yield (September)				
Boll weight	−0.59*	−0.65*	ns	−0.46
Closed bolls (%)	−0.46	−0.55*	ns	−0.48

*$P < 0.01$, ns – not significant.

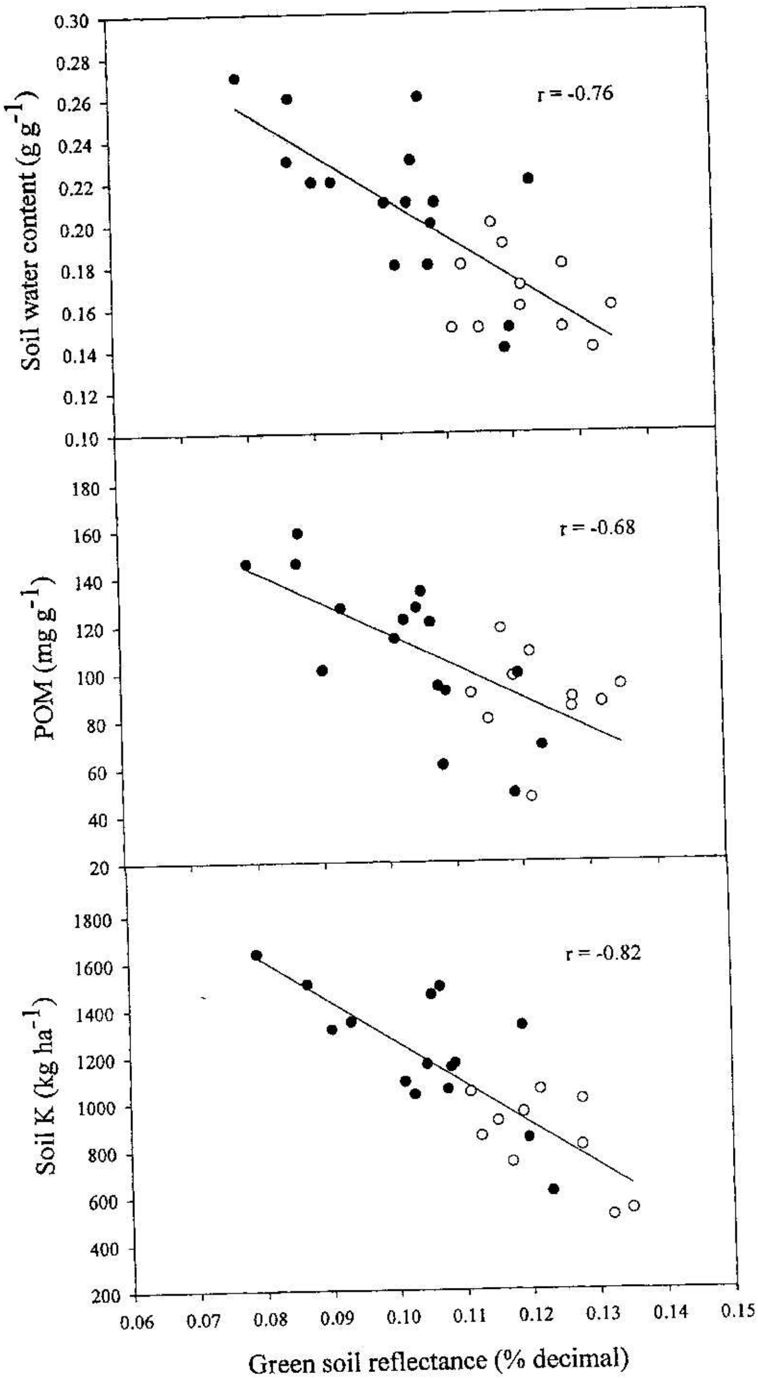

Figure 2. The negative relationship of surface soil reflectance to soil water content, particulate organic matter and extractable soil K on the east side (closed circles) and on the west side (open circles) of the field.

content or POM to soil NIR reflectance was significant, but considerably lower than that to blue or green soil reflectance (Table 3). The negative correlation of extractable soil P and K with soil reflectance may be related to the fact that soils with higher organic matter levels may also have higher levels of mineralized nutrients. The higher correlation coefficients of these soil nutrients with the blue and green soil reflectance are in agreement with Varvel *et al.* (1999) who found significant relationships between Bray-1 P and soil brightness values in the blue, green and NIR bands from a bare soil image in a Haplustoll near Shelton (Nebraska, USA).

The red and NIR region of the spectrum was more sensitive to soil carbonate content that resulted in strong positive correlations (Table 3, Figure 3). High carbonate content was associated with soil erosion on the west side of the field that may indirectly explain the negative correlation of red and NIR reflectance with soil EC and N content. Soil carbonates were also found by Khalil *et al.* (1997) to have a positive correlation with soil reflectance in the same soil order (Entisol) in Egypt. Thus, carbonates appear to be an important factor that influences soil reflectance in eroded calcareous soils of the Mediterranean region.

Among the four bands of soil reflectance, only the red band was significantly correlated to canopy reflectance when all data were included in the analysis (Figure 3). The correlation of red soil reflectance with the visible bands of canopy reflectance was positive (r = 0.56 to 0.59, n = 32), and with NDVI negative (r = −0.58, n = 32), which implies an inverse relationship between soil fertility and plant stress. This is because plant stress results in increased visible or reduced NIR reflectance (Pinter *et al.*, 2003) while high carbonate and eroded field positions

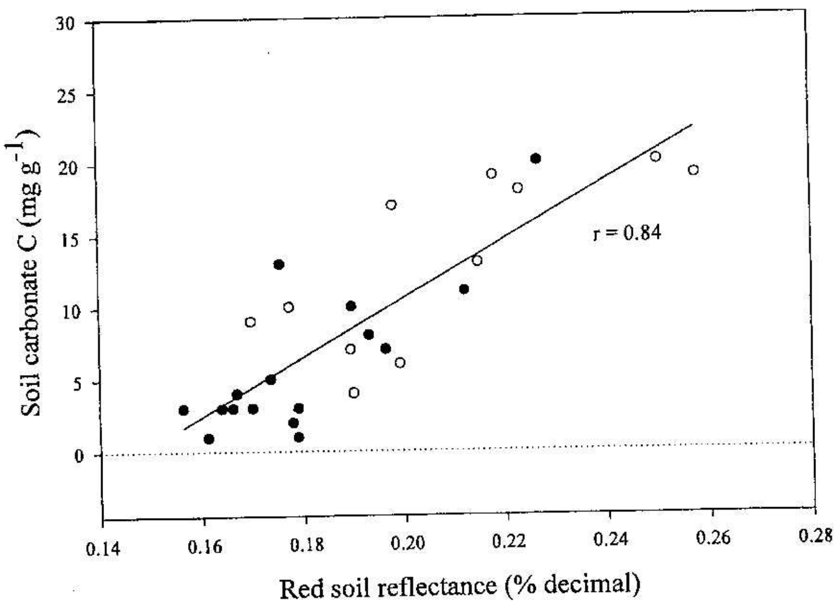

Figure 3. The positive correlation of surface soil reflectance to carbonate content on the east side (closed circles) and on the west side (open circles) of the field.

resulted in increased red soil reflectance (Figure 3). In our study, evidence for plant stress came from the positive correlation of canopy NDVI to cotton biomass, and for low soil fertility from the negative correlation of carbonate content to soil nutrients and organic matter content (data not shown). Such an indirect relationship between soil reflectance and plant stress may also explain the negative correlation of soil reflectance in the red and NIR bands with leaf N and P (Table 3). A closer examination of the relationship between soil and canopy reflectance revealed that the correlation of soil reflectance with NDVI was higher and the slope of the regression was greater on the east side of the field (Figure 4). This inconsistency appears to be caused by differences in soil reflectance between the high carbonate positions of the two sides of the field (see also Figure 3).

In theory, the integration of the different information provided by surface soil reflectance and by indicators of plant response may give a more reliable prediction of soil properties in the root zone (Barnes *et al.*, 2003). This hypothesis was tested in a multiple regression model where individual soil properties (0–0.3 m depth) composed the dependent variable while soil reflectance and plant response variables, i.e. canopy reflectance, nutrient status and biomass, were the independent variables. The results, shown in Table 4, indicate that only a single independent factor was able to explain a substantial portion of the spatial variability of soil properties in the root zone. Most of the variability explained by the model for water content and properties related to soil organic matter (SOM) such as POM, total N and extractable P and K, was explained by soil brightness in the blue, green and red bands (Table 4). The same was true for carbonates as most of their variability in the field (r^2 = 0.70) was explained by soil brightness in the red region of the spectrum. The overall r^2 of the

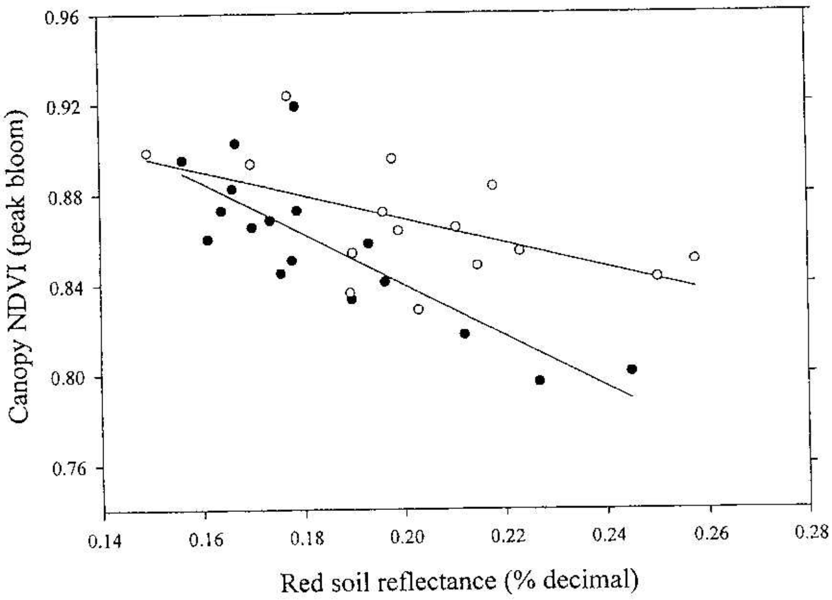

Figure 4. The negative relationship of surface soil reflectance to canopy NDVI on the east side (closed circles, r = −0.82) and on the west side (open circles, r = −0.56) of the field.

Table 4. Proportion of variability (r^2) explained by soil reflectance and plant response variables in multiple regression for the prediction of soil properties (n = 26, p = 14)[a] The ratio of peak bloom to mid square was used as an integrator of leaf reflectance

Independent variables		SOM-related variables					Indicators of nitrification			
		Water content	POM	Total N	Extract. P	Extract. K	CO_3-C	EC	NO_3-N	pH
Soil reflectance	Green[b]	0.58	0.46	0.19	0.39	0.67	–	–	–	–
	Red	–	–	0.31	–	–	0.70	–	–	–
	NIR	–	–	–	–	–	–	0.07	–	–
Leaf reflectance	NDVI	–	–	–	–	–	–	–	–	0.08
Leaf nutrients[c]	N	–	–	–	–	–	–	0.60	0.42	0.47
	K	–	–	–	–	–	0.08	–	0.10	–
Biomass	Above ground	–	–	–	0.12	–	–	–	–	–
	Closed bolls (%)	0.07	–	–	–	0.06	–	–	–	–
Model r^2		0.65	0.46	0.50	0.51	0.73	0.78	0.67	0.52	0.55

[a]n = number of observations, p = number of parameters including the intercept.
[b]Green was used as a proxy variable for blue reflectance due to their high correlation (r > 0.80).
[c]Leaf nutrients in August.

regression model was significantly increased, although not by much, by cotton biomass in the cases of water content and soil P and K (Table 4). The positive correlation of soil water content with the proportion of closed bolls (r = 0.67, n = 33) indicates the importance of soil water in prolonging the period of boll maturation in this field.

Among the three measures of crop response, only crop nutrient status explained a substantial portion of the model variability for soil properties related to soil nitrification and acidification. In particular, late-season leaf N content explained a significant portion of the variability of soil EC, pH and nitrate-N (Table 4). This is an example of the importance of crop nutrient status in explaining the spatial variability of soil properties in the root zone. However, the relationship was only evident late in the growing season, after exhaustion of the soil mineral N supply, especially on the west side of the field. This information should be applicable to certain types of agricultural management of this field in subsequent years. On the other hand, soil reflectance data (taken in June) can be used to construct maps of soil properties that may find applications to site-specific management where corrective measures need to be taken at an early stage during the growing season.

Conclusion

The data provided evidence of the potential of ground sensors to predict basic soil properties and plant stress from bare soil reflectance in different regions of the VNIR spectrum. The integration of surface soil reflectance and plant response variables in a multiple regression model did not substantially improve the prediction of soil properties in the root zone. However, crop nutrient status explained a significant portion of the spatial variability of soil properties related to nitrification processes when soil reflectance did not.

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